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Statistical modeling of charcoal consumption of blast furnaces based on historical data

Rosiane Mary Rezende Faleiro[a,b,*], *Cláudio Musso Velloso*[b], *Luiz Fernando Andrade de Castro*[a], *Ronaldo Santos Sampaio*[c]

[a] *Department of Metallurgical and Materials Engineering, Universidade Federal de Minas Gerais, Belo Horizonte, MG, Brazil*
[b] *Raw Material and Hot Metal Production Department, V & M do Brasil, Belo Horizonte, MG, Brazil*
[c] *RSConsultants Ltda., Itabirito, MG, Brazil*

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ABSTRACT

This paper describes the development of statistical models to predict charcoal consumption in blast furnaces based on Response Surface Models (RSM) and Linear Regression Models (LRM). The statistical approach used provides a high level of confidence and allows the company to act preemptively fostering innovative business and in the action plan to reduce hot metal production cost, to improve raw materials processing and other actions in order to provide the blast furnaces with raw materials at minimal cost. It is a special particularity and represents a great step in V & M do Brasil blast furnaces' operation which no longer uses standard ferrous load and started to operate with greater flexibility and variability concerning the types of ferrous load applied to achieve better economic results.

1. Introduction

The main objective of a blast furnace is to reduce chemically and convert physically iron oxides into liquid iron, which is called hot metal. Hot metal manufacturing process consumes about 70% of the entire energy of steel manufacturing integrated route. Besides, social and industrial needs for iron and steel, high prices of raw materials and reducing agents have also increased the necessity to model and control this complex process in order to increase productivity and reduce costs. However, internal phenomena of hot metal manufacturing are extremely challenging for human mind. This is due to several reasons, such as high temperatures and pressure; various phases occurring simultaneously and their interactions; time, mass and energetic exchanges, which hinder direct measurements of many variables in the blast furnace [1].

In order to obtain suitable conditions for thermal control, permeability and hearth exhaustion, to promote an efficient and steady operation, with high productivity and low consumption of reducers, it is essential to acquire information about control parameters through metering equipment or, in some cases, through the development of mathematical [2,3], statistical [1,4–9], thermodynamical [1,10], kinetic [11] models, among others [12–16].

* *Corresponding author.*
E-mail addresses: rosiane@vmtubes.com.br, rosianefaleiro@yahoo.com.br (R.M.R. Faleiro).
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An important statistical model is known as "Flint Formula," an algebraic expression that allows the correlation between carbon specific consumption (coke-rate) and a large number of process variables of hot metal manufacturing in blast furnace [4]. Due to large variations in process and raw materials qualities of charcoal blast furnaces, no statistical model has ever been applied [12]. A similar attempt to apply "Flint Formula" to charcoal blast furnaces of non-integrated plants was made in 1990 [6]. Taking into account the low process stability, and the lack of reliability on measured operational data, it was not possible to establish a correlation of process variables with the specific carbon consumption of the charcoal blast furnaces from these plants. Other statistical models were implemented in coke blast furnaces, for example, the correlation developed in 1991 [17], which related a smaller number of variables than that of "Flint Formula". Probably, the referential blast furnace in this study had very stable operation, with little variation in the process, hence the efficiency for the specific carbon consumption calculation.

Since 2008, V & M do Brasil has been carrying out studies to reduce hot metal production cost, using historical data on raw materials consumption and hot metal production in the blast furnaces. Afterwards, these data are turned into information that can be used to evaluate production cost and achieve better planning and results for the company.

2. Materials and methods

V & M do Brasil hot metal is basically produced by employing iron ore, pellet and charcoal. The plant is equipped with two blast furnaces: Blast Furnace 1, with a volume of 505 m^3, and Blast Furnace 2, with 249 m^3. The maximum production capacity of both blast furnaces is 600,000 t/year. On average the percentage of pellet used in the blast furnaces' mix varies from 25 to 60%, and the average injection rate of charcoal fines is 170 kg/t hot metal.

The high uncertainty of physical and chemical features of charcoal, the use of iron ore with significant heterogeneity, the great influence of the climate on quality and uncertainties of raw materials sampling hinder the use of thermochemical models. While this variability is to be minimized with the use of better technologies of carbonization and resources for raw materials processing, it is necessary to use statistical tools [18].

Projects using Six Sigma methodology were developed in V & M do Brasil to quantify and reduce the variability of charcoal and iron ore sampling process in order to obtain more reliable results. Through these studies, it was estimated that about 20% of the total variability of these materials is due to sampling procedures (collection, preparation and analysis).

Charcoal, iron ore and pellet that fuel V & M do Brasil blast furnaces are routinely assessed in terms of moisture, particle size, chemical compositions, and then quality improvement is carried out. Iron ore is beneficiated at the processing plant where firstly homogeneous piles are made; secondly, iron ore is dried; finally, it is screened to remove fines. And charcoal is also screened to remove fines; the thick remaining part is sorted into two ranges of particle size [19].

The database used to construct the models consists of daily real information about consumption in both blast furnaces, chemical and physical quality results of charcoal, iron ore and pellet, from May 2003 to December 2011. During data processing, the "outliers" were excluded, which are the days when there were shutdowns or reconnection blast furnaces, since these could interfere in the adequacy of the fitted models.

Table 1 – Parameters used in the development of statistical models.

Parameters	Unities
Response	
Charcoal consumption	kg/t hot metal
Variables (or factors)	
Production	t hot metal
Injection rate	kg/t hot metal
Type of iron ore	%
Pellet	%
Season	
Rainy (November to March)	1
Dry (April to October)	0

The statistical approaches used to model and analyze the data were Response Surface Models (RSM) and Linear Regression Models (LRM), chosen because they are useful in applications where the interest response, in this case charcoal consumption (kg/t of hot metal), is influenced by many variables (or factors) and the objective is to optimize this response [20]. Given the fact that, V & M do Brasil has two blast furnaces with very different characteristics, it is necessary to work with information from each blast furnace and adjust specific models for each of them.

The shape of a surface response is viewed by three-dimensional graphics known as contour plots or contour lines. In most RSM problems, it is unknown how the relationship is between response and independent variables. Therefore, the first step is to identify a more accurate approximation of this relationship. A low degree polynomial is generally used if the response variable is well modeled by a linear function of variables. Then the approximation function will be the first-order model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (1)$$

where y = response; x = variables (or factors), β = regression coefficients and ε = errors with normal distribution, mean 0 and standard deviation σ.

If there is curvature, then a higher degree polynomial has to be used as the second-order model:

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{i<j} \sum \beta_{ij} x_i x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \varepsilon \quad (2)$$

In order to estimate beta coefficients, Least Squares Method [20] is applied, which is the same method used to estimate regression coefficients in Multiple Linear Regression Models.

Blast furnaces' consumption parameters used in the fitted models are summarized in Table 1.

Data were grouped into sets according to the ferrous load composition, i.e. into groups of days with similar percentages of ferrous load consumption (% of each type of iron ore and % of pellet). In total, 88 different sets were defined for Blast Furnace 1 and 147 different sets for Blast Furnace 2.

Averages and standard deviations of parameters response and variables were obtained for each set regarding the rainy season (January, February, March, November and December) and the dry season (April, May, June, July, August, September and October). For each set there was also an addition of quality parameters, which are the average charcoal quality results: fixed carbon (%), ash (%), moisture (%), fines less than 10 mm (%), average particle size (mm). For the total ferrous load the parameters are: iron (%), alumina (%) and silica (%).

RSM were constructed for each blast furnace for the rainy and dry seasons using MINITAB statistical software, considering single, quadratic and interactional effects of variables listed in Table 1 along with quality parameters of charcoal and the ferrous load. Therefore, it was considered a significance level of 10% in hypothesis tests for beta coefficients to determine whether a parameter was significant or not and whether it should remain or be removed from the model.

Once the best model for each blast furnace is defined, with the highest multiple determination coefficient R^2, which is used as a measure to fit the model [20], the next step was to prepare contour plots considering both parameters variation (x- and y-axes) and fixing the others, based on actual values already used in the blast furnaces. The response "charcoal consumption" is visually differentiated by colors in the contour plots and measured in values ranges.

In order to facilitate the use of information from the contour plots, the midpoint of each graph was used to develop LRM. Firstly, models were developed to predict the percentage of pellet according to daily production (t) of hot metal. Then, models were developed to predict charcoal consumption (kg/t of hot metal) in relation to percentage of pellet used in total ferrous load.

3. Results and discussion

3.1. RSM

The best fitted RSM, considering only significant effects at a significance level of 10%, showed R^2 of 88.3% and 87.1% for Blast Furnace 1, in the rainy and dry seasons, respectively; and 76.2% and 70.0% for Blast Furnace 2, in the rainy and dry seasons, respectively. Models residuals were analyzed and complied with the requirements of normal distribution, mean around zero and constant variance, as required by the statistical model.

3.2. *Contour plots*

Contour plots, as shown in Fig. 1, have been prepared considering the x-axis "Pellet (%) used in the ferrous load" and the y-axis "Iron (%) used in ferrous load". The response "Top charcoal consumption," is visually differentiated in the contours and is represented in percentage in relation to "Total charcoal consumption (top + injection + loss)."

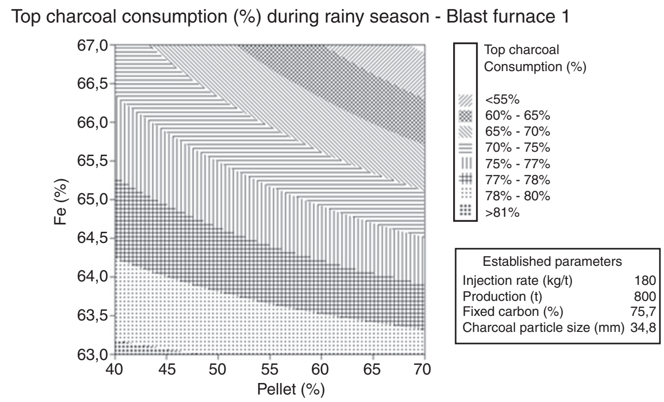

Fig. 1 – Example of contours plot.

In order to construct a contour plot as demonstrated in Fig. 1, the x- and y-axes must contemplate actual value ranges of operation and the other RSM parameters must be established. For instance, 800 t/day to produce hot metal in Blast Furnace 1, during the rainy season, it is possible to use from 40 to 70% of pellet, while iron content in the total ferrous load might range from 63 to 67%. The established values for the other model parameters were: injection rate of 180 kg/t, fixed carbon of 75.7% and charcoal particle size of 34.8 mm. For these values, the plot shows that the higher the percentage of pellet and the iron content in the ferrous load are, the lower the top charcoal consumption is. Considering percentages in relation to total charcoal consumption, which is the sum of top, injection and loss, the top consumption in this example ranges from 55% to 81% in relation to total consumption.

These curves allow the company to estimate immediate costs and they are strategically used in front of offers and market opportunities of pellet and iron ore with immediate financial return in order to achieve better economic results.

3.3. *LRM*

In order to facilitate the use of information from the contour plots before providing with the monthly and annual planning of hot metal production and the consumption of ferrous load and charcoal in blast furnaces, all midpoints of several contour plots were collected to develop LRM.

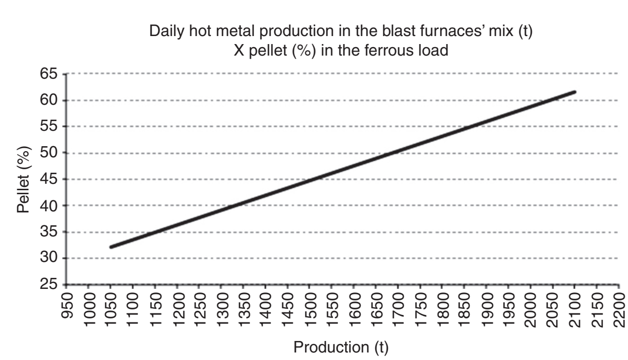

Fig. 2 – Model that determines the percentage of pellet to be used in the blast furnaces' mix in relation to daily hot metal production (t).

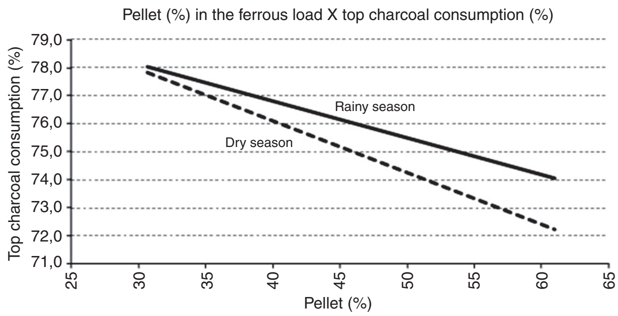

Fig. 3 – Model that determines top charcoal consumption (%) based on percentage of pellet to be used in the blast furnaces' mix.

Based on blast furnaces daily production plan, the first step is to determine the percentage of pellet to be used in the blast furnaces. LRM were developed as in Fig. 2, which shows the existence of a significant positive correlation ($R^2 = 97.8\%$) between hot metal daily production (t) and the percentage of pellet to be used in ferrous load. To put it in a general way, the higher the production, higher will be the percentage of pellet to be used in the blast furnace.

Once the percentage of pellet in the ferrous load is defined, the next step is to estimate charcoal consumption. Fig. 3 illustrates the developed models per season, rainy and dry, which estimate top charcoal consumption (% in relation to total charcoal consumption) based on the percentage of pellet used in the blast furnaces ferrous load.

Highly accurate developed models have been used to set targets for the consumption of charcoal and ferrous load since January 2012. The average difference between actual charcoal consumption in 2012 and the estimate given by the models is 1.04%.

4. Conclusions

The statistical approaches used, RSM and LRM, are in the domain of technical and scientific community. However, the application of these approaches seeking the development of a model to estimate charcoal consumption in blast furnace, using hot metal production historical data and ferrous loads consumption has never been done before.

In addition, developed models are highly accurate, so the company is able to act preemptively fostering innovative business and in the action plan to reduce hot metal production cost, to improve raw materials processing and other actions in order to provide the blast furnaces with raw materials at minimal cost. Meanwhile the development of new charcoal manufacturing technologies to improve the quality and homogeneity of charcoal is still in progress.

In conclusion, the work developed pioneered the use of statistical approach in charcoal blast furnaces, and it is a great step in blast furnace operation, with special particularity for V & M do Brasil blast furnaces' operation, which no longer uses standard ferrous load and started to operate with greater flexibility and variability concerning the types of ferrous load applied to achieve better economic results.

Conflicts of Interest

The authors declare no conflicts of interest.

REFERENCES

[1] Gao C, Chen J, Zeng J, Liu X, Sun Y. A chaos-based iterated multistep predictor for blast furnace iron making process. AIChE J 2009;55:947–62.
[2] Liu X, An T. Mathematical Modeling of Closed-loop Intelligent Control for B.F. Iron-making Process. icicta. In: Fourth international conference on intelligent computation technology and automation, vol. 1. 2011. p. 438–41.
[3] Shur AB. Dynamics models of blast furnace smelting for trainers and researchers. Metall Alch 2008;52:141–7.
[4] Flint RV. Multiple correlation of blast furnace variables. In: Tambasco MJ, editor. Blast furnace, coke oven and raw materials conference, 11, 1952. AIME apud. Redução de minério de ferro em alto-forno, 11, 1952. 4th ed. São Paulo: Associação Brasileira de Metais; 1977. p. 49–73.
[5] Lian P, Ning N, Aiping C, Yaobin T. Fault diagnosis of the blast furnace based on the Bayesian network model. In: ICECE' 10 proceedings of the 2010 international conference on electrical and control engineering. 2010. p. 990–3.
[6] Mapa GMO, Castro LFA, Filho OD. Controle estatístico de processo aplicado a produção de gusa em usinas não integradas a carvão vegetal. Congresso anual da associação brasileira de metais, vol. 54. Rio de Janeiro. Anais. . .São Paulo: ABM; 1990. p. 25–140.
[7] Pan W, Liu S, Zeng J, Gao C. A refined prediction model of silicon content based on the Kalman Filter. In: Chineses control conference. 2010. p. 3153–6.
[8] Thomson EPR. Controle do processo de produção do alto-forno por meio de técnicas estatísticas multivariadas [MsD Tesis in Statistics]. Belo Horizonte: UFMG; 2005. p. 180.
[9] Zeng J, Liu X, Gao C, Luo S. Subspace method of identification and control of blast furnace ironmaking process. In: American control conference, 2008, Washington. 2008. p. 2481–5.
[10] Tshumura K. Modeling for control of blast furnace. In: International conference on control applications. 1999. p. 1–6.
[11] Druckenthaner H, Scheidl J, Schürz B. VAI blast furnace automation – a powerful solution for highest production economy. In: Annual meeting. 1997. p. 2182–6.
[12] Castro LFA. Desenvolvimento de um modelo de controle de processo para altos-fornos a carvão vegetal [PhD Tesis in Metallurgical Engineering]. Belo Horizonte: Escola de Engenharia da UFMG; 2002. p. 155.
[13] França AB, Feiteira JFS, Castro JA. Utilização de redes neurais artificiais e modelo CFD como estratégia para tomada de decisões no processo do alto-forno. In: 39° Seminário de redução de minério de ferro e matérias-primas Ouro Preto. 2009.
[14] Soares MI, Carvalho DHD, Bayer DS. Modelagem do nível térmico de um alto-forno para aumento da eficiência operacional utilizando redes neurais artificiais. In: 39° Seminário de redução de minério de ferro e matérias-primas Ouro Preto. 2009.
[15] Souza JB, Kankamby NH, Lockwood FC. Aplicações da mecânica dos fluidos computacional na indústria

siderúrgica. In: 39° Seminário de redução de minério de ferro e matérias-primas Ouro Preto. 2009.
[16] Qiu D, Zhang D, You W, Zhang N, Li H. An application of prediction model in blast furnace hot metal silicon content based on neural network. IEEE 2009:61–4.
[17] Bhagat RP, Ray HS, Gupta SK. Improvement in performance of the blast furnace at Bhilai through statistical analysis and improvement in burden preparation. ISIJ Int 1991;31: 669–76.
[18] Sampaio RS, Pinheiro PCC, Rezende MEA. Exigências metalúrgicas para o carvão vegetal em mini altos-fornos e fornos elétricos de redução. In: Seminário: Prática, Logística, Gerenciamento e Estratégias para o Sucesso da Conversão da Matéria Lenhosa em Carvão Vegetal para Uso em Metalurgia e Indústria. 2006.
[19] Cruz JG, Barroso RC. Fabricação de ferro gusa em altos-fornos a carvão vegetal. Belo Horizonte: Associação Brasileira de Metalurgia e Materiais; 2007. p. 108.
[20] Montgomery DC, Runger GC, Hubele NF. Estatística Aplicada à Engenharia. 2nd ed Rio de Janeiro: LTC; 2004. p. 335.